IMPROVING CREDIT SCORES FOR INDIVIDUALS AND SMALL BUSINESSES: IMPLICATIONS FOR DIGITAL BANK'S CREDIT RISK

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BY

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A final year project submitted in partial fulfilment of the requirement for the degree of

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DECLARATION

I hereby declare that:

(1) This undergraduate FYP is the end result of my own work and that due acknowledgement has been given in the references to ALL sources of information be they printed, electronic, or personal.

(2) No portion of this FYP has been submitted in support of any application for any other degree or qualification of this or any other university, or other institutes of learning.

(3) Sole contribution has been made by me in completing the FYP.

(4) The word count of this research report is 11978.

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Date: 29/4/2024

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DEDICATION

This study report will be dedicated to my supervisor, Ms. Loh Yin Xia, as a token of appreciation, as she tolerates and guided me every process of the way on my Final Year Project journey. As well as the perspective she provided always helps me open the door to new ideas.

In addition, this report will also be dedicated to my father, Mr. Yu Ming Ngee, who has been continuously supporting me with good living conditions, as a comfortable space for conducting research without external disruption.

Lastly, I would like to dedicate my final year project to friend, Nick Lau, who has provided banking information and market perspective to help further explore my mindset.

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PREFACE

According to the requirements of the University Tunku Abdul Rahman (UTAR) for the award of certificates for the Bachelor of International Business (Honours), it is a pre-condition that every student undertakes the final year project, ‘UKMZ2016 Research Project'. There are plenty of research topics that can be conducted by the student of international business, as the course for this programme includes a very wide range. As for this study, the author’s final year project title is "Improving Credit Scores for Individuals and Small Businesses: Implications for Digital Bank’s Credit Risk". This is because the author has noticed that the demand for inferior goods and services in Malaysia has increased, resulting in the emergence of many small-cost entrepreneurial groups; this has a great opportunity for digital banks that specialize in small loan packages to gain market share. Therefore, formulating a guideline can optimize the efficiency of interaction between users and digital banks. For digital banks, it can quickly refine the user base. For users, a clear understanding of the guidelines can effectively establish a good credit score and make it easier to obtain loans.

ABSTRACT

The rapid growth of digital banking has revolutionized the financial landscape globally, presenting novel opportunities and challenges for individuals and businesses alike. This study investigates the implications of improving credit scores for individuals and small businesses, particularly focusing on the context of digital banks' credit risk in Malaysia. The research methodology employs a descriptive approach, utilizing secondary data sourced primarily from Indian digital banking platforms, considering their emerging relevance to the Malaysian market.

Challenges pertaining to data availability, quality, and applicability are identified, stemming from the nascent stage of digital banking in Malaysia and the cross-border nature of the data sources. Despite these limitations, the study endeavors to provide valuable insights into the relationship between borrowers' credit profiles and digital banking practices. Findings from exploratory factor analysis, Pearson correlation analysis, and descriptive statistics offer nuanced perspectives on the factors influencing credit scores and loan profiles in the digital banking domain.

Theoretical implications underscore the evolving dynamics of credit assessment methodologies within the digital banking paradigm, while practical implications highlight the potential for enhancing risk management strategies and financial inclusion initiatives. Limitations inherent in the study, including data accessibility constraints and the need for further validation, are acknowledged, yet they do not diminish the significance of the findings. Instead, they serve as catalysts for future research endeavors aimed at unraveling the complexities of digital banking ecosystems and fostering sustainable financial practices. Through a comprehensive examination of credit scoring mechanisms and loan profiles, this study contributes to the broader discourse on digital finance and its transformative impact on financial services provision in emerging markets like Malaysia.

Chapter 1: Research Overview

1.1 Introduction

This chapter will thoroughly cover all fundamental details relevant to the entire study, including the background of the research, the questions it aims to address, its objectives, and importantly, the significance of the research.

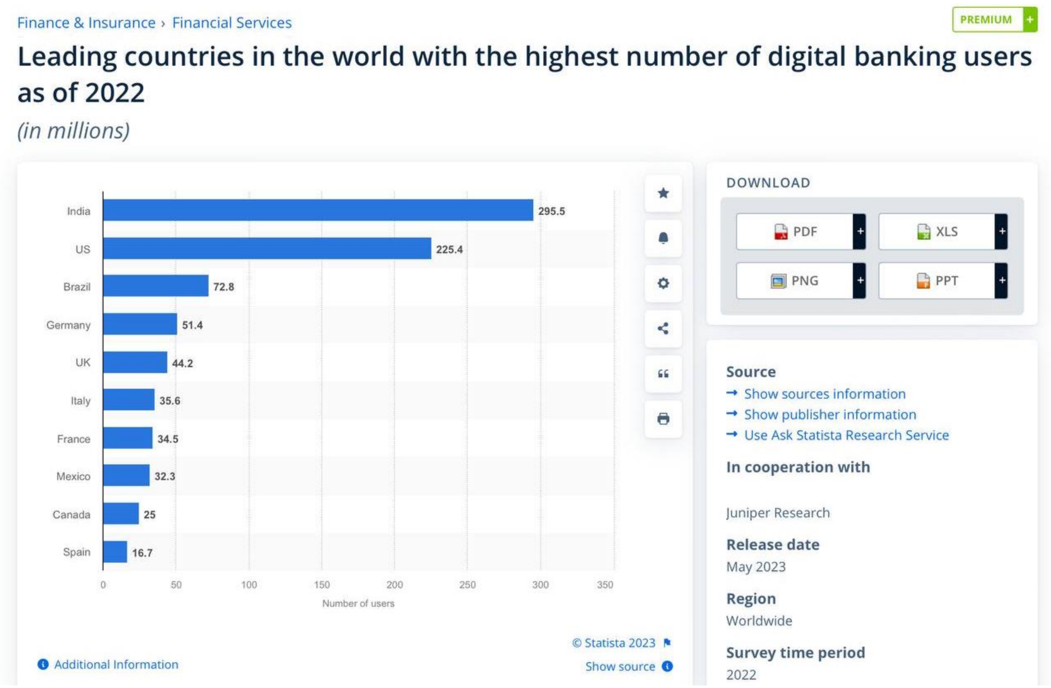
1.2 Research of Background

The traditional banking industry used to rely heavily on physical branch operations and face-to-face interactions between customers and bank representatives for transactions such as deposits, withdrawals, and loan applications, usually documented in paper format (Davies, Richardson, Katinaite, & Manning, 2010). However, the emergence of electronic banking, including technologies like ATMs and telephone banking, marked a significant shift in the banking landscape (Guru, Vaithilingan, Ismail, & Prasad, 2000). These innovations enabled customers to conduct transactions beyond traditional banking hours and locations, offering them greater convenience. As internet technology continued to mature, the introduction of online banking platforms further revolutionized the banking paradigm. These online banking platforms allow customers to remotely engage in various banking activities through web-based interfaces, encompassing basic transactions, account management, and access to financial information, significantly enhancing convenience (Nitsure, 2003).

In recent years, the advent of digital banks has brought about a revolutionary change in the financial industry where this change fundamentally alters the way financial services are delivered and accessed. They provide comprehensive financial services via digital channels, leveraging cutting- edge technologies such as mobile applications, data analytics, and artificial intelligence to deliver seamless, user-centric experiences (Indriasari, Gaol & Matsuo, 2019). This transformation is particularly crucial for enhancing financial inclusivity, catering to underserved, and underbanked populations, and fostering a more inclusive economy (Vong, Mandal, & Song, 2016).

Recent global data shows a surge in digital banking, especially in mobile usage. However, adoption rates vary due to factors like infrastructure, regulations, and socio-economic conditions.

Figure 1.1 Top 10 Countries Worldwide with Highest Number of Digital Banking Users 2022



Source: Statista Research Department 2023

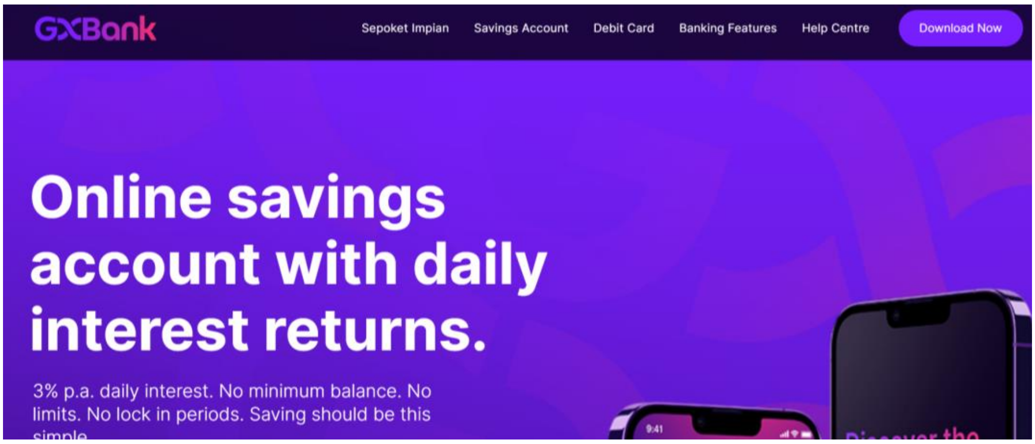
The statistics reveal current specific trends in several major countries, indicating a gradual but significant shift towards digital banking solutions. As shown in Figure 1.1, India's user base surprisingly reached 295.5 million,while the United States ranked at 225.4 million. India's rise in digital banking is due to the Indian government's active promotion of digital finance; after becoming the world's most populous country, India has a demographic dividend of mostly young adults. Also benefiting from government promotion, India's fintech usage rate is 87%, far exceeding theglobal average (64%) (Lin, 2023). The most critical thing is that in 2016, India's Startup Indian plan provided a lot of financial and non-financial support, including providing simplified registration procedures, providing credit, capacity improvement and other plans (Lin, 2023). The second key thing is that Covid-19 in 2019 directly caused the usage of Digital Bank to surge (Lin, 2023).

However, the systems in European and American countries have long beenmature but are growing slowly, which may mean that many European and American digital banks may still face challenges such as credit assessment efficiency and user credit background.

At the same time, other emerging economies such as Asia Pacific and South Asia that are not on the list may have potential future development scenarios.

Currently in Malaysia, in the last quarter of 2023, Boost-RHB Digital Bank,Aeon Bank Bhd, and Grab-Led GXBank have carried out a Joint-Venture strategy and jointly launched Malaysia's first digital bank-GXBank. The bank currently only launches Online Savings Program (Debit Card), the reason may be to obtain monthly turnover to build users' credit report and reduce the risk at the same time.

Figure 1.2 GXBank Online Saving Plan Program



Source: GXBank Malaysia

1.3 Research Problem

The rapid rise of digital banks has brought transformative convenience. However, this evolution has limited the development of digital banking andraised barriers to adoption for users.

Digital banks that rely on innovative data analytics and technology for lending decisions face unique challenges in accurately assessing credit risk(Huang et al., 2020).

For example, one of the main challenges in credit risk assessment in digitalbanks is customer classification and verification of their creditworthiness (Witzany, 2017). Not only that, but digital banks also usually implement small-amount loans as their main business; therefore, emerging digital banks have a large number of micro-enterprises and individuals who lack good credit records or financial records, which makes it difficult for banks to accurately assess their credit risks.

Furthermore, users of digital banking services may lack awareness of how their behaviours and actions affect their credit scores, leading to unforeseenconsequences and negative outcomes (Witzany, 2017). For example, users may not know the factors that affect their credit scores or how to improve their credit scores, thereby not thinking about the consequences of irregularbehaviour, ultimately leading to suboptimal credit decisions (Witzany,2017).

By addressing these issues, this study aims to improve the understanding ofdigital bank credit assessment while providing guidelines of improving credit scores to strengthen and deepen the bond between users and digital banks.

1.4 Research Objectives

The objectives of this research are to aim to address the challenges of credit risk assessment and credit score improvement in digital banking, with a focus on micro-enterprises and individuals.

1. To identify the key factors influencing the credit score improvement process for individuals and small businesses.
2. To provide a guideline of Digital Bank Credit Scoring for Small Businesses and Individuals in Malaysia.

1.5 Research Questions

The research questions that induce from this study include:

1. How do Small Businesses and Individuals improve the credit profile without a well-established credit history?
2. How do different type of financial behaviours, such as bill payments or credit utilization, affect credit score improvement for individuals and small businesses?

1.6 Research Significance

Due to the global economic slowdown, Malaysian consumers are extremelysensitive to the price (Chemat, 2024); hence, many consumers start to look for cheaper alternatives, such as Shein against Uniqlo & Zara. Meanwhile, the higher services tax and increased prices of raw materials impact many industries (Chemat, 2024). Not only that, the massive increase in demand for low-cost housing in Malaysia also illustrates the current lowering of theoverall income level of consumers (Zainun, 2015).

When secondary demand arises, the market will flood into many small-cost businesses. For example, the demand for mid-to-high-end restaurants has decreased, and they may face closed down due to high decoration and operating costs; however, many small vendors will appear in shopping malls, night markets, hawker centre and other places through stalls, food trucks, etc.

Most of the owners of these emerging small-cost enterprises lack a complete credit profile, so they will face high interest repayments when borrowing from physical banks. At the same time, in the early days of digital banks, it was difficult to perform lending services without user credit information; even if they were implemented, they would face high risks of default.

Therefore, the insights from this study will provide a reference for enhancing credit risk management strategies to digital bank. Regulators and policymakers can use these findings to develop more targeted guidelines and regulations. Moreover, this is also beneficial to small and medium-sized enterprises and the government, because these evaluation standards can provide precise guidance for the government to formulate support plans for local enterprises. Guided local business support initiatives can therefore stimulate economic growth and market creativity.

1.7 Summary

In this chapter, we explore the historical development of the banking industry, from the past to the present day, with the emergence of consumer downgrading giving rise to a new business model - digital banking. This model not only changes the way the banking industry operates, but also poses new challenges to users (including individuals and small businesses): loans have become more difficult and cumbersome. In addition, emerging digital banks lack sufficient user information and have difficulty accurately assessing users' credit levels, which results in both parties facing a high-risk situation.

Chapter 2: Literature Review

2.1 Introduction

This chapter will delve into relevant journal articles pertinent to our study. Initially, we'll examine the foundational theory, namely the FICO model. Subsequently, we'll analyze aspects such as Credit Score, Assets and Liabilities Status, Income Level, Loan Profile, Financial Behavior, Financial Needs, Purpose of Loan, and Payment History. Additionally, a research framework has been devised for this study.

2.2 Underlying Theory

2.2.1 FICO Model (Fair Isaac Corporation Model)

At the end of the 19th century, with the rise of mass retail and department stores, consumer credit reports began to appear and were used to evaluate consumers' credit information (Paul, 2023). FICO Score, founded in 1956, launched the FICO Model in 1989, a credit scoring model that can be used to assess the credit status of all consumers (Paul, 2023). So far, FICO has been continuously updated and iterated to FICO Model 10, among which FICO Model 8 is still the most popular and is widely used in fields such as car loans, credit cards, and mortgage loans (FICO Scores Versions, n.d.). This FICO score is based on a three-digit range from 300 to 850 and is used to score a user's credit report; a score of 700 and above is considered a good credit score; a score of 580-660 are considered a fair credit score (What is a Credit Score, n.d.).

Currently, FICO Model is widely used by companies in more than 90 countries, including the famous American Express, UBS, MasterCard, African Bank, P&G, etc. In Malaysia, most private companies use the FICO

Model, such as Credit Guarantee Corporation Malaysia (FICO Customers, n.d.).

FICO scores are analysed by using different credit data in the credit report, such as payment history, income level, liabilities status, credit account balance, credit mix, purpose of loan, bankruptcies, and other information. This data can be categorized into five main groups: payment history, outstanding balances, credit account age, recent credit inquiries, and types of credit used. (What is in my FICO Scores, n.d.;Thinh, 2017).

2.3 Review of Variables

2.3.1 Variables Brief

(DV) Credit Score: Amount Annuity Previous (Loan annuity in previous application and paid as result)

(IV1) Asset and Liabilities Status: Flag Own Realty (Flag if client owns a house or flat)

(IV2) Income Level: Amount Income Total (Client's Total Income Yearly)

(IV3) Loan Profile: Amount Credit (Final credit amount of the loan Yearly)

(IV4) Financial Behaviour: Amount Goods Price (For consumer loans, it refers to the cost of the items that the loan is intended for, Yearly)

(IV5) Financial Needs: Amount Application Previous (How much credit did client apply initially in previous application)

(IV6) Purpose of Loan: Amount Goods Price Previous

(IV7) Payment History: Amount Credit Previous and Paid

The description is stated in the data set.

2.3.2 Credit Score (DV)

The credit score serves as a crucial metric in the financial sector, assessing the credit risk of individuals and businesses. It significantly impacts loan approval, determination of interest rates, and access to financial products. Individual credit scores typically involve an analysis of payment history, borrowing situations, and other financial behaviours (Mester, 1997, p. 4). Meanwhile, corporate credit scores, besides financial indicators such as losses rate, profitability; it may also encompass factors like operational history, market performance (Řezáč & Řezáč, 2011, p. 487).

In previous studies, the credit scores of individuals and businesses have been found to be closely associated with loan default rates and credit risks. According to Agarwal et al. (2011), individuals transitioning out of infancy face a higher risk of bankruptcy and loan defaults, with bankruptcy and loan default rates up to 15% and 17% higher, respectively, compared to other categories of individuals. Meanwhile, Lundqvist et al. (2016) indicated that lower business credit scores are linked to increased corporate default risk or overall business risk. Factors contributing to corporate risk management include current macroeconomic conditions, financial ratios, among others.

Personal credit scores are affected by many factors, including payment history, debt levels, educational background, etc. (Perry, 2008). In contrast, corporate credit scores may be influenced more by factors such as revenue performance, industry trends, credit risk management, probability of default, and so on (Saygili, Saygili, & Isik, 2019).

Therefore, strategies to enhance individual and corporate credit scores involve fostering good payment habits, managing debt, and increasing financial transparency. These strategies not only aid in boosting credit scores and improving loan terms but also significantly assist in pre-employment screening for individuals (Arya, Eckel, & Wichman, 2013).

2.3.3 Assets and Liabilities Status

In accounting and finance, assets refer to resources or rights owned by an individual or company that can be used to bring economic benefits in the future, such as cash, cars, real estate, etc (Schuetze, 2002). Liabilities are debts or obligations owed by individuals or companies, such as loans, accounts payable, etc. These conditions are critical because they reflect financial health and financial risk. Not only that, the age of the asset will also suffer losses as the years go by, which is especially reflected in the assets related to cars (Schuetze, 2002).

Research by Bhuvaneswari et. al (2014) pointed out that car ownership is an important factor in the credit risk model; therefore, vehicle ownership can measure financial stability and purchasing power, so vehicle ownership is closely related to creditworthiness. Similarly, the results of this study can also positively indicate that real estate, as a real estate that is more expensive than cars and less likely to depreciate, can also measure financial stability and average consumption levels. Financial stability is an important indicator of credit score.

2.3.4 Income Level

Albanesi, DeGiorgi, and Nosal (2017) contend that a robust correlation exists between credit scores and income, with income emerging as the primary factor influencing changes in credit scores even when age is taken into account. However, this high correlation leads to an exacerbation of income inequality, widening the gap in access to credit and further deepening the inequality in consumption and welfare. Yet, Beer, Lonescu, and Li (2018) suggest that the level of income for consumers is only moderately correlated with their credit scores. This is due to the existence of a significant population with low credit scores among high-income individuals and vice versa, with high credit scores also among many low-income individuals. Therefore, it is considered that individual and household income should not be solely relied upon as primary factors for assessing credit scores.

Figure 2.1: Table (Log Income-Credit Score Correlations in Subpopulations)

	Whole Sample	Marital Status		Educational Attainment		Sample Period	
	(1)	Single (2)	Married (3)	College degree (4)	No college degree (5)	2007-12 (6)	2013-17 (7)
All ages	0.290	0.273	0.266	0.279	0.246	0.276	0.312
65 and younger	0.380	0.357	0.363	0.313	0.357	0.388	0.370
66 and older	0.270	0.256	0.225	0.217	0.249	0.268	0.282

Source: Board of Governors of the Federal Reserve System

In Figure 2.1, since most consumers over 66 years old have retired, their income is not closely related to financial resources and credit risk, so they are not taken into consideration. Here, it is shown that the income of married people (0.363), which means that there are at least two people in the family relationship, is more positively related to credit scores than the income of single people (0.357).

2.3.5 Loan Profile

Loan profile analysis involves evaluating the financial and personal information of borrowers, contract types, balance information, credit amounts, and specific purposes within the loan portfolio to assess their creditworthiness and likelihood of loan repayment (Loan Profile Information Definition, 2014). Lenders utilize this analysis to make informed decisions on whether to approve loan applications and what terms to offer.

In the study of Soman and Cheema (2002), it was found that information such as credit limit is used to explain consumers' future earning potential.

For instance, when a consumer has extensive access to credit, it suggests that their expected lifetime earnings are substantial, leading to a heightened inclination to utilize credit, reflected in increased spending.

According to Ahmed and Rajaleximi (2019), the higher credit amount is usually come with higher interest rate when the borrower does not have credit history or well-built credit profile. They consider higher interest amount will cause higher probability of default as it encompasses the penalty for owing higher risk.

2.3.6 Financial Behaviour

Financial behavior refers to the actions and choices taken by individuals or entities in finance-related decisions and activities. These behaviors and choices cover a range of financial activities, including saving, investing, lending, spending, and more. Financial behavior reflects the attitudes, preferences and practices of individuals or entities in managing financial resources, coping with risks, and achieving financial goals (Henager & Cude, 2016). Research and analysis of financial behavior can help understand the financial health, risk tolerance, consumption habits, investment behavior, etc. of an individual or entity, and provide an important reference for formulating financial planning and decision-making for individuals or organizations (Henager & Cude, 2016).

The level of spending a person or business spends on goods or services can have an impact on your credit score. This level of spending often reflects the borrower's spending habits and financial situation. However, research by Greene (1992) indicate that excessive or unreasonable spending levels may have a negative impact on credit scores, and the impact is that consumers are more likely to default on their loans.

2.3.7 Financial Needs

Financial needs refer to the financial products, services, and resources that individuals, families, businesses, or other entities need to achieve their financial goals and cope with financial challenges in life, business or other aspects. These needs may include savings, investments, borrowing, credit, insurance, tax planning, etc (Remund, 2010; Reed, 2023).

Argawal, Alok, Ghost and Gupta (2020) found that households in rural areas or low-income families borrow an average of US$250 per year for education, investment in small businesses, replenishing inventories, house repairs, etc. They also found that these types of loans were widespread. To reduce risks, banks carry out risk management through social ties for these families without credit history. Through social ties, banks can screen customers with high creditworthiness.

2.3.8 Purpose of Loan

Loans for various purposes carry different risk profiles, with certain loan purposes—such as home mortgages—posing specific risks. The varying timelines for repayment of these loans also increase the probability of default and credit risks. According to Fatemi and Fooladi's research in 2006, loans with longer repayment timelines and larger amounts often face the highest default risk, such as complex derivative-based transactions in car loans. This is due to the possibility that accidents involving the car during the repayment period could diminish the borrower's desire or ability to repay.

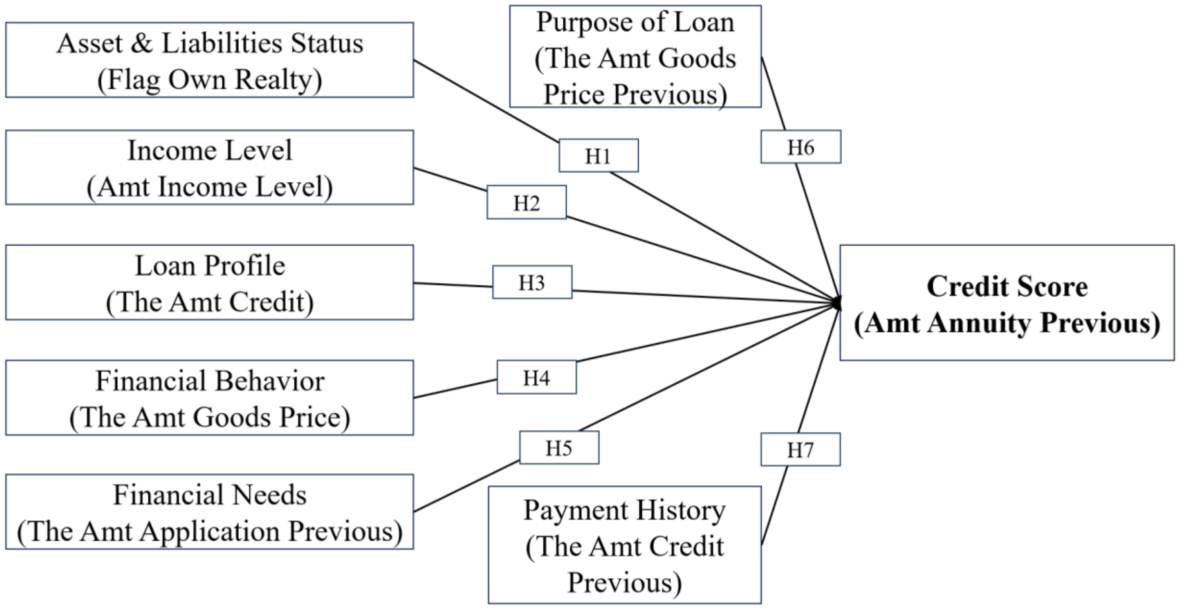
Most of the different types of fraudulent loans use small loans and false information reporting to defraud large amounts of loans (Chen et al, 2022). It is mentioned in the study that past purchase orders (purpose, consumption preference) can be used as audit indicators for large-amount loans to test the detection model (Chen et al, 2022).

2.3.9 Payment of History

Avery, Calem, and Canner (2004) study found that payment history, amounts owed, and length of credit history were associated with credit scores. This reflects the borrower's financial stability and ability to repay. In the study of Wilson et. al (2010), it was pointed out that past payment behavior is an important indicator for predicting the probability of personal or business failure in the future, because this data can be used to predict future payment behavior and consider interest rate adjustments. Also, through the customer's payment history and background history, the probability of the customer repaying the loan can be calculated (Ahmed & Rajaleximi, 2019).

2.4 Conceptual Framework

Figure 2.2: Proposed Research Framework



Source: Developed for the Study

2.5 Hypothesis Development

This section develops hypothesis for this study.

2.5.1 Assets and Liabilities Status

The conclusion of Schuetze (2002) shows that assets and liabilities reflect financial health and financial risks and therefore can be used as important indicators. Not only that, research by Bhuvaneswari et al. (2014) pointed out that car and real estate ownership can measure financial stability and purchasing power; therefore, assets and liabilities are important factors in credit risk models.

H1: The relationship between assets & liabilities status and credit score.

2.5.2 Income Level

Albanesi et al. (2017) believe that income is the most important determinant of credit score changes. However, Beer et al. (2018) shows that there is only a moderate correlation between a consumer's income level and their credit score due to there are many people with large differences bias in credit scores among high- and low-income people.

H2: The relationship between income level and credit score.

2.5.3 Loan Profile

Soman and Cheema (2002) found that data such as credit limits can suggest a person's potential for high lifetime income and, consequently, their inclination to utilize credit for spending. Next, the research of Ahmed and Rajaleximi (2019) shows that a higher credit amount is accompanied by a higher interest rate and a higher probability of default, thus affecting the credit score.

H3: The relationship between loan profile and credit score.

2.5.4 Financial Behaviour

Research by Henager et al. (2016) shows that financial behavior reflects the attitude and preferences of individuals or entities in managing financial resources and coping with risks. Therefore, behaviors such as consumption habits, expenditure levels and investments can be used as important references for credit score (Henager et al., 2016).

In addition, research by Greene (1992) shows that unreasonable expenditures may be a precursor to loan defaults, ultimately affecting credit scores.

H4: The relationship between financial behavior and credit score.

2.5.5 Financial Needs

Research by Remund (2010) and Reed (2023) pointed out that through financial needs, we can understand the financial planning and use of funds by individuals, families, businesses or other entities; therefore, these plans can determine the size of the credit amount and the level of interest. and other factors to avoid default, ultimately affecting credit score. In addition, Argawal et al. (2020) found that small-amount loans are common and have high default rates, thus affecting credit scores through social relationship binding.

H5: The relationship between financial needs and credit score.

2.5.6 Purpose of Loan

Research by Fatemi and Fooladi (2006) pointed out that credit packages intended for larger borrowing amounts and longer repayment times tend to have high default rates, such as the possibility of complex derivatives transactions in car loans. In addition, frequent small loans or preferences for different purposes may be suspected of fraud (Chen et al, 2022).

H6: The relationship between purpose of loan and credit score.

2.5.7 Payment of History

Research by Avery et al. (2004) pointed out that payment history, amount owed, and length of credit history reflect financial stability and repayment ability; therefore, they can be used as important indicators of credit scores. In studies by Wilson et al. (2010) and Ahmed et al. (2019), it was concluded that past payment behavior can be used to predict future payment behavior and the probability of loan repayment.

H7: The relationship between payment of history and credit score.

2.6 Summary

In this chapter, the meaning of all variables is defined; at the same time, hypotheses are established for each independent variable. Furthermore, a research framework is developed to clearly predict the relationship between dependent and independent variables.

Chapter 3: Research Methodology

3.1 Introduction

This chapter will discuss definition about secondary data. Additionally, secondary data sources, sampling design, data sampling, and suggested data analysis tools will be elaborated in this chapter.

3.2 Research Design

A research design refers to the comprehensive framework or arrangement that directs the course of research activities. It plays a crucial role in shaping the research process, outlining the methodology and strategies for gathering and analysing data, essentially serving as a roadmap for executing a study (Jain N., 2023). Descriptive research refers to a methodology employed to depict existing phenomena with precision where the phenomena are already observable and accessible within the context of descriptive research (Atmowardoyo, 2018). In this research, a descriptive research design will be employed to comprehensively investigate the landscape of improving credit scores for individuals and small businesses, with implications for digital banks' credit risk. Leveraging secondary data, the research will involve the analysis of historical credit score data, financial reports, and pertinent literature to gain a nuanced understanding of creditworthiness dynamics. This approach will allow for the identification and description of key factors influencing credit scores, such as financial behaviour, payment history, and debts level.

Through descriptive research, this study aims to identify key variables influencing creditworthiness, compare credit scores across different segments, and create a detailed profile of credit risk management practices within the digital banking sector. By providing a holistic overview, descriptive research contributes valuable insights that can inform decision-making processes for digital banks, guiding the development of effective strategies and interventions to address credit risk and foster credit score improvement. The findings are expected to support informed decision-making within digital banks, guiding the development of policies, interventions, and strategies to better address the financial needs of their clients.

3.3 Sampling Design

A sampling design outlines a structured approach to selecting a subset from a specific population. It encompasses the method or process that a researcher intends to use in selecting elements for the sample. Additionally, the sample design may also specify the quantity of items to be incorporated into the sample, known as the sample size (Lohr, 2021).

3.3.1 Target Population

The target population refers to the specific set of people whom the intervention aims to study and derive conclusions from through research (Gregory, Stevens, & Fraser, 2018). The elements of the target population are individuals and small businesses engaged in financial transactions with digital banks in Malaysia. Individuals may include consumers with various credit histories and financial behaviors, while small businesses encompass a range of enterprises across different industries and sizes in Malaysia. The selection of this target population is justified by the study's focus on credit score improvement and providing a guideline for small business entrepreneurs without credit history to establish.

3.3.2 Sampling Frame

The sampling frame consists of databases, records, or lists containing information about individuals engaged in banking activities, such as previous loan amount, annuity amount and so on.

3.3.3 Sampling Technique

A sampling method is the approach employed to choose a portion of individuals or items from a broader population to be included in a research investigation or survey (McCombes, 2019). The objective of employing a sampling method is to guarantee that the sample accurately reflects the characteristics of the population under investigation, thereby enabling the extrapolation of findings from the sample to the broader population.

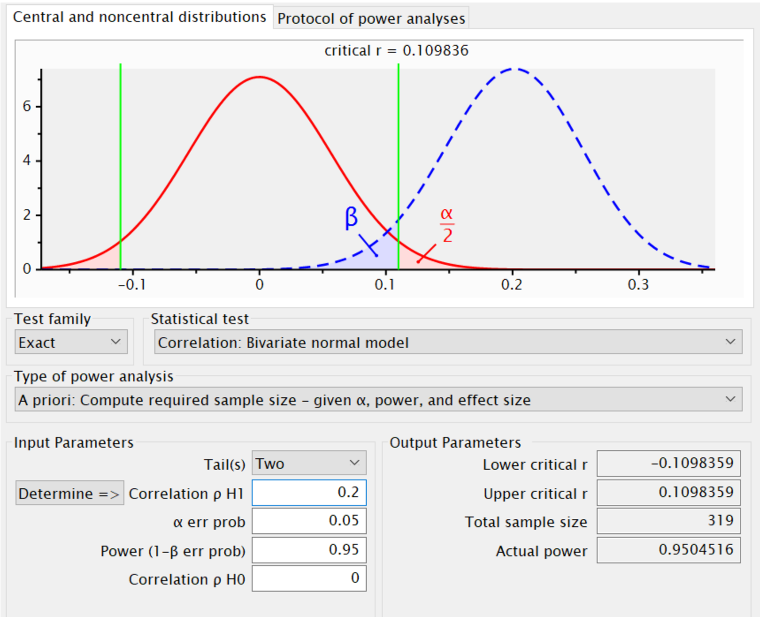
In this study, a simple random sampling technique is utilized to select applicants from the target population of individuals and small businesses engaging with bank. Simple random sampling involves selecting individuals from a population in such a way that each member has an equal chance of being chosen for the sample, and the selection of one member does not affect the selection of others (Thomas, 2020). According to Sharma (2017), through simple random selection, bias in the selection process is mitigated since every member of the population has an equal opportunity to be chosen. Simultaneously, simple random sampling ensures that every individual or unit in the population has an equal chance of being included in the sample. This helps in creating a representative sample that accurately reflects the characteristics of the entire population (Sharma, 2017).

3.3.4 Sampling Size

Sample size denotes the quantity of individuals, items, or units chosen for participation in a research investigation or survey from the broader population of interest (Psycol Med, 2020). Typically, a greater sample size has the potential to enhance the precision and inclusiveness of the sample. However, it necessitates additional time, labour, and resources for both gathering and analysing data. Conversely, a smaller sample size might be more feasible but could yield less dependable and less broadly applicable outcomes (Lakens, 2022). Therefore, it's essential to assess the informativeness of the data for inferential tasks like determining an effect size or conducting hypothesis testing.

G Power Calculator is utilized in this research, a statistical software tool widely employed in research for estimating statistical power and determining samples sizes (Kang, 2021). Researchers could use it in establishing the smallest sample size needed to detect a statistically significant impact, based on specific assumptions regarding effect size, alpha level, and power (Kang, 2021). With 95% of confidence level and 5% of margin error, the minimum sample suggested is figured at 319 applicants. Figure 3.1 shows the calculation outcome of G*Power Calculator.

Figure 3.1: Calculation Outcome from G*Power Calculator



Source: Developed for Study

3.4 Data Collections Methods

Data collection involves the systematic gathering, measurement, and analysis of dependable insights, employing standardized and validated techniques to enhance accuracy and reliability (Bar-Ilan, 2001). The secondary data will be utilised to study on the factors that influence the credit score of individuals and small entrepreneurship man in this research project. As a result, secondary data will be utilised to analyse information as it provides higher level accuracy of payment history and key information.

3.4.1 Secondary Data

Secondary data refers to non-original data used by researchers when conducting research, but data that has been collected, organized, or published by others (Church, 2002). These data are often collected by government agencies, research institutions, academic institutions, or other organizations during previous studies, surveys, or projects, and are then used by other researchers for new research purposes. Secondary data can include various types of data, such as survey data, statistical data, literature, text data, image data, etc (Church, 2002).

Utilizing secondary data for research has many advantages, including saving time and costs, providing a perspective on historical data and long-term trends, and providing broader data coverage (Hofferth, 2005). However, using Secondary data may also face some challenges. For example, the quality of the data may be inconsistent or incomplete, the background and collection methods of the data may not be transparent, and the availability and applicability of the data may be limited (Perdana, Surya, Eddy, & Ramadhani, 2022).

3.4.2 Sources of Secondary Data

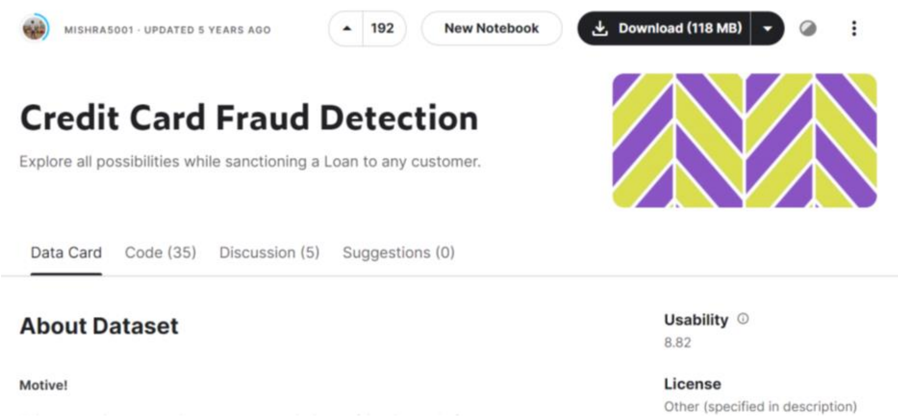
Kaggle is a renowned platform for data science competitions and community-driven data set sharing. It offers a wide array of publicly accessible data sets spanning diverse fields like computer vision, natural language processing, finance, healthcare, and more. Therefore, researchers can use datasets on Kaggle in their studies to support their analysis and research purposes. Although data sets on Kaggle are usually uploaded and shared by users rather than published by professional organizations, the Kaggle community will conduct a certain degree of review and verification of the quality and reliability of the data. In addition, data sets on Kaggle usually provide data descriptions, source information, and explanations of data fields to help users understand the background and content of the data.

Regarding the authenticity of Kaggle data sets, some academic papers and research reports have cited data sets on Kaggle and verified and analysed the data in research. Typically, these documents acknowledge where the dataset originated from and detail the methods used to process the data, ensuring its trustworthiness and precision.

3.4.3 Reliability of Data

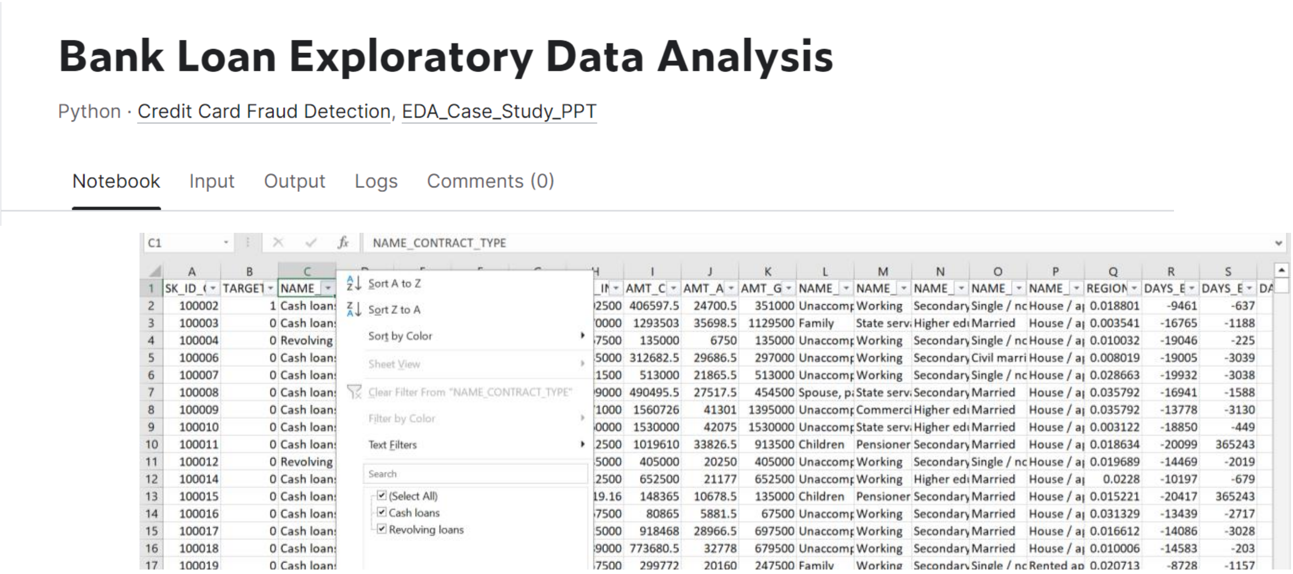
This study leverages Kaggle's publicly available loan dataset as the primary data source, which is derived from personal and small business loan information reported by IIIT Bangalore. Although we do not directly cooperate with banks, these data sets are officially collected and published by professional institutions and are highly certified by Kaggle officials (8.2/10) (refers to Figure 3.2), so they have high reliability. This data was originally collected as part of a social experiment, which was originally intended to provide public inferences about how people who applied for loans completed the loan in the shortest time. Therefore, the data can be used as an indicator to provide a perspective of small businesses or Individuals in Malaysia on how to improve their credit score quickly while applying to digital bank loan.

Figure 3.2 Data Sources from Kaggle



Source: Kaggle

<u>Figure 3.3 Data Details from Sources from Kaggle</u>



To further discuss about IITT Bangalore, Indian Institute of Technology, Bangalore (IIT Bangalore) is one of the famous Indian Institute of Technology, located in Bangalore, southern India. Founded in 1961, the college is one of the top engineering and technology education institutions in India and an important member of the Indian engineering college system. IIT Bangalore is known for its excellent teaching quality, world-class research output and excellent alumni network. The college has a first-class faculty team and is committed to providing high-level undergraduate and postgraduate education to train students to become internationally competitive engineering and technical talents. IIIT Bangalore has achieved recognition as one of India's leading technical universities, securing a position in the top 10 according to the August 2020 edition of India Today (IIITB ATTAINS TOP 10 RANKING AMONG INDIA'S TECHNICAL UNIVERSITIES, 2021).

3.4.4 Suitability of Data

This study uses loan records provided by IITT Bangalore as the main data source. These data mainly include personal and small business loan amounts, repayment annuities, annual total income, region, job positions and other information.

We found in this data that individuals and small businesses borrowed a wide range of amounts, from the smallest amounts (45,000 INR, approximately MYR 2,600) to the largest amounts (over 2 million INR, approximately MYR 114,500). The wide range of borrowing amounts likely reflects the demand for different sizes and types of loans in the market. Some borrowers may only require a smaller amount to meet short-term funding needs, while others may require a larger loan for business expansion or investment. Likewise, differences in risk appetite may mean that some borrowers may be more willing to take on smaller loans, while others may be willing to take on larger loans because they have different repayment abilities or credit histories. Not only that, but records also show that many borrowers intend to start with a small amount to establish a good repayment record so that they can obtain a larger amount in the next loan application.

This finding further confirms our research hypothesis that individuals and small businesses may have certain constraints on their borrowing needs and may be more inclined to use short-term loan instruments such as credit cards to build credit history in the short term. Therefore, we will further analyze these loan records to explore the relationship between the loan situation of individuals and small businesses and their credit scores.

Although these data have many advantages, we also need to consider their limitations. For example, loan records may not cover all individuals and small businesses, and there may be issues with sample bias. In addition, because the data only come from specific financial institutions, they may not reflect the situation of other financial institutions, affecting the generalizability of the research results. Therefore, when interpreting the study results, we will fully consider these limitations and provide corresponding discussions and suggestions to enhance the credibility and reliability of the study.

3.4.5 Adequacy of Data

The data for this study comes from the loan record database provided by IITT Bangalore (Kaggle), which includes information such as loan amount, application amount, repayment annuity, and purpose of borrowing. Our sample includes borrowers from different regions and industries, with a total of 319 samples. The sample was selected based on the loan records of the National Bank using a simple random sampling method. We believe that this sample is representative and able to support our research purposes.

When assessing the adequacy of the data, we found that the quantity and quality of the data were adequate for our research needs.

3.5 Data Processing

Before conducting any analysis, certain computational procedures need to be completed. Egger (2008) suggests that the aim of data processing is to refine the data for improved comprehension. Additionally, the data processing procedure encompasses tasks such as data checking, data coding, data transformation, data integration as well as data cleaning.

3.5.1 Data Checking

Data checking is a critical step in the data processing process to ensure data accuracy, completeness, and consistency. During the data checking phase, the researcher will conduct a comprehensive review and verification of the collected data to identify and correct possible problems or errors (Barchard & Verenikina, 2013).

3.5.2 Data Cleaning

During the data inspection process, researchers may find some data errors or anomalies that need to be cleaned and corrected. This includes operations such as removing duplicate data, correcting erroneous data, and filling in missing data (Ilyas & Chu, 2019). Hence, some duplicated and missing value will be removed.

3.5.3 Data Integration

Data integration involves amalgamating data from various origins or structures into a cohesive data repository. This process can include collecting, cleaning, transforming, and integrating data for better analysis, reporting and decision-making (Lenzerini, 2002, June). After verifying the data provided by the SKU ID, the loan applicant's history and current loan record are integrated, making the current application stage clearly visible.

3.5.4 Data Coding

Data coding involves transforming the original qualitative data gathered by the researcher into a coded format. This coding assigns numerical values to the responses provided by participants, facilitating their grouping together (Linneberg & Korsgaard, 2019). For this research, the Flag Own Realty of "Yes" will be coded as "1" while "No" will be coded as "0".

3.5.5 Data Transformation

Data transformation refers to processing raw data in a specific way to facilitate subsequent analysis, modelling or visualization (Data Transformation , 2010). Using log transformation to normalize data when the data has a skewed distribution, or the variance is unstable. Log transformation can make the data closer to a normal distribution, thereby improving the interpretability of the data and the performance of the model (Changyong et al., 2014). Hence, the IVs (The Amt Income Level, The Amt Credit, The Amt Goods Price, The Amt Application Previous, The Amt Credit Previous, The Amt Goods Price Previous) and DV (The Amt Annuity Previous) both be log transformed as the amount having extreme value.

3.6 Proposed Data Analysis Tool

This section proposes the data analysis tool that be utilized in this research.

3.6.1 Descriptive Analysis

Descriptive analysis involves thoroughly describing and examining collected data, typically through tables, graphs, charts, or similar methods (Lawless & Heymann, 2010). In this research, data collected in histogram format from SPSS will be organized into tables. This analytical approach aids in simplifying the data to a manageable level, facilitating the research process.

3.6.2 Inferential analysis

Pearson's correlation coefficient and Exploratory Factor Analysis will be utilized in this study.

3.6.2.1 Pearson's Correlation Coefficient

The Pearson correlation coefficient gauges both the intensity and orientation of a linear connection between the variables that are dependent and independent. It provides a value between -1 and 1 that represents the degree of correlation between two variables (Malaghan, 2022).

Table 3.1 Rules of Thumb about Correlation

Correlation Coefficient	Correlation's Strength
0.00 *to* 0.10	Very Weak
0.11 *to* 0.39	Weak
0.40 *to* 0.69	Moderate
0.70 *to* 0.89	Strong
0.90 *to* 1.00	Very Strong

Source: Malaghan, 2022

Multiple variables were involved in this study, including credit score (Amt Annuity Previous) and other influencing factors (such as Amt Credit, Amt Income Level, Amt Goods Price, etc.). By using the Pearson correlation coefficient, we can explore the linear relationship between these factors and the credit score to understand how correlated they are.

3.6.2.2 Exploratory Factor Analysis

The main function of Exploratory Factor Analysis (EFA) is to help researchers understand the latent structure in the data, identify potential factors that may exist, and discover latent structures (Baldner & McGinley, 2014). For example, EFA can help us determine which variables are more related to each other.

Not only that, but the role of communalities is also to distinguish the size to eliminate invalid or weak variables and select more powerful variables to explore the association (Birmingham, 2017). According to the work by Birmingham City University, the items with less than

0.2 should be removed. According to MacCallum (1999), the acceptable communality for retained variable is at least 0.5 for sample size more than 200 (MacCallum et al., 1999).

3.7 Summary

In this chapter, the utilization of secondary data as the chosen research methodology is elucidated. Furthermore, the researcher delineates the origins of the data, the design of the sampling, and the processing of the data. Lastly, the proposed tool for data analysis is also specified.

Chapter 4: Data Analysis

4.1 Introduction

In this section, information gathered from secondary sources will be organized and displayed in accordance with the research methodology detailed in Chapter 3. The procedure begins with scrutinizing the data, then arranging demographic data, and finally examining the outcomes through descriptive and inferential analysis techniques.

4.2 Data Screening

In this study, we utilize all 319-person financial information that have been recorded by the original author. The 319 data was collected as part of Social Experiment, where it covers the past and current payment of loan and amount, as well as other relevant information.

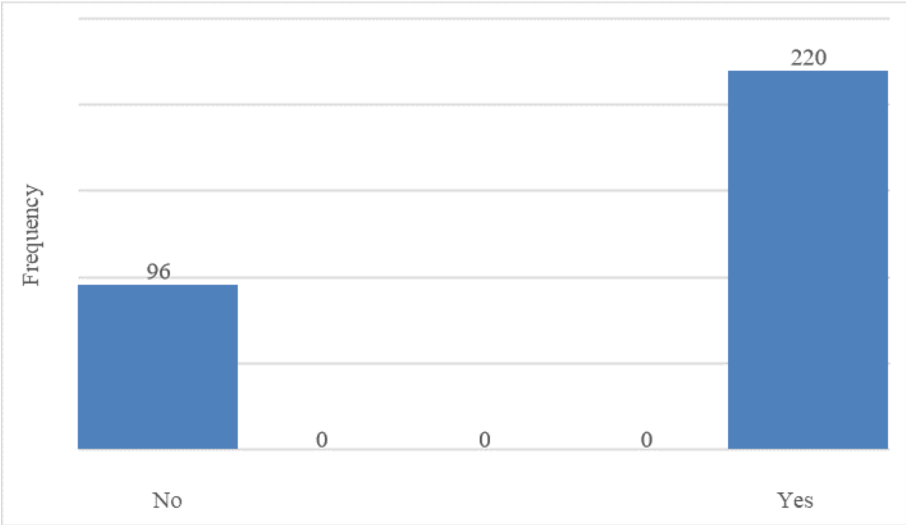
4.3 Descriptive Analysis

In this section, there are 7 variables will be mainly illustrated and provide additional findings from the secondary sets for further analysis use.

4.3.1 Assets and Liabilities Status (Flag Own Realty)

The realty ownership status of applicant is shown in Figure 4.1 and Table 4.1.

Figure 4.1 The Flag Own Realty



Source: Adopt from Secondary Data

Table 4.1 The Flag Own Realty

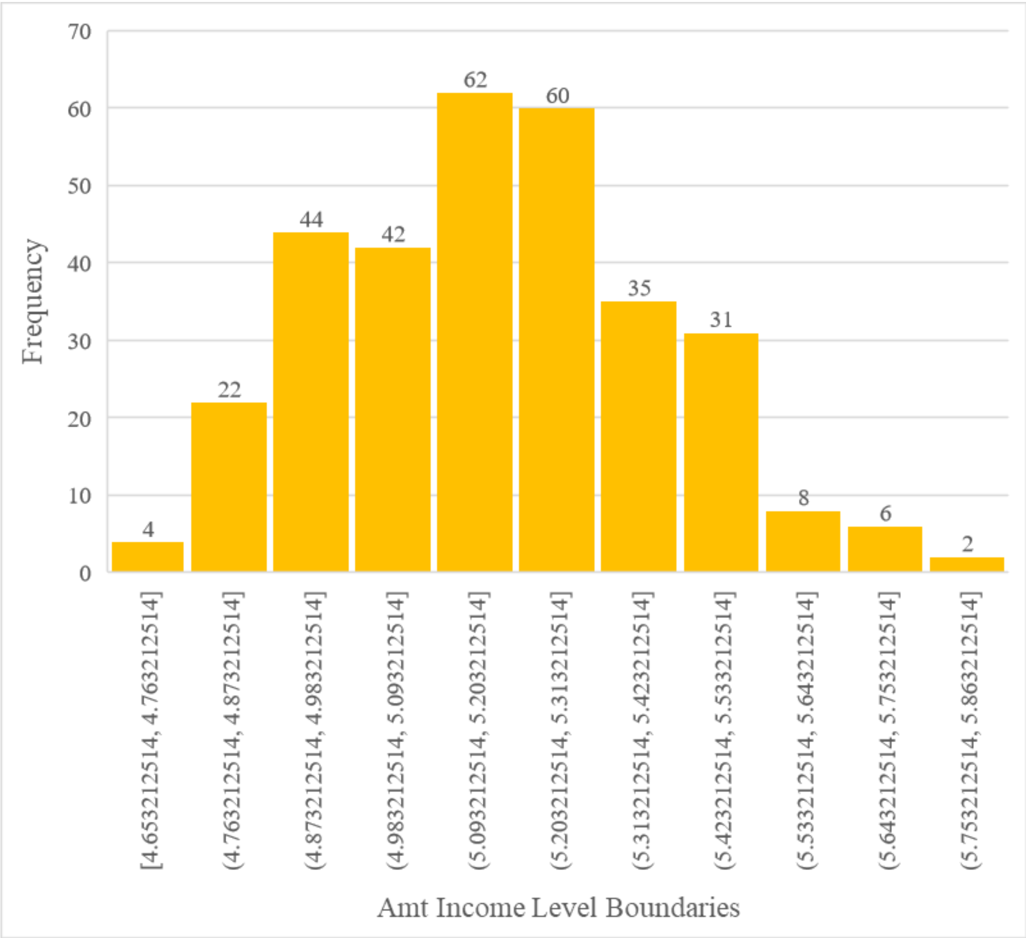
	Frequency	Percentage
Yes	220	69.62%
No	96	30.38%
Total	316	100%

Source: Adopt from Secondary Data

Based on the data collected, most of the applicants (69.62%) are having realty, 30.38% of applicants are not having any realty.

4.3.2 Income Level (Amount Income Total)

Figure 4.2 The Amt Income Total



Source: Adopt from Secondary Data

Table 4.2 The Amt Income Total

Income Level Boundaries	Frequency	Percentage
(4.65, 4.76)	4	1.27%
(4.76, 4.87)	22	6.96%
(4.87, 4.98)	44	13.92%
(4.98, 5.09)	42	13.29%
(5.09, 5.20)	62	19.62%
(5.20, 5.31)	60	18.99%
(5.31, 5.42)	35	11.08%
(5.42, 5.53)	31	9.81%
(5.53, 5.64)	8	2.53%
(5.64, 5.75)	6	1.90%
(5.75, 5.86)	2	0.63%
Total	316	100%

Source: Adopt from Secondary Data

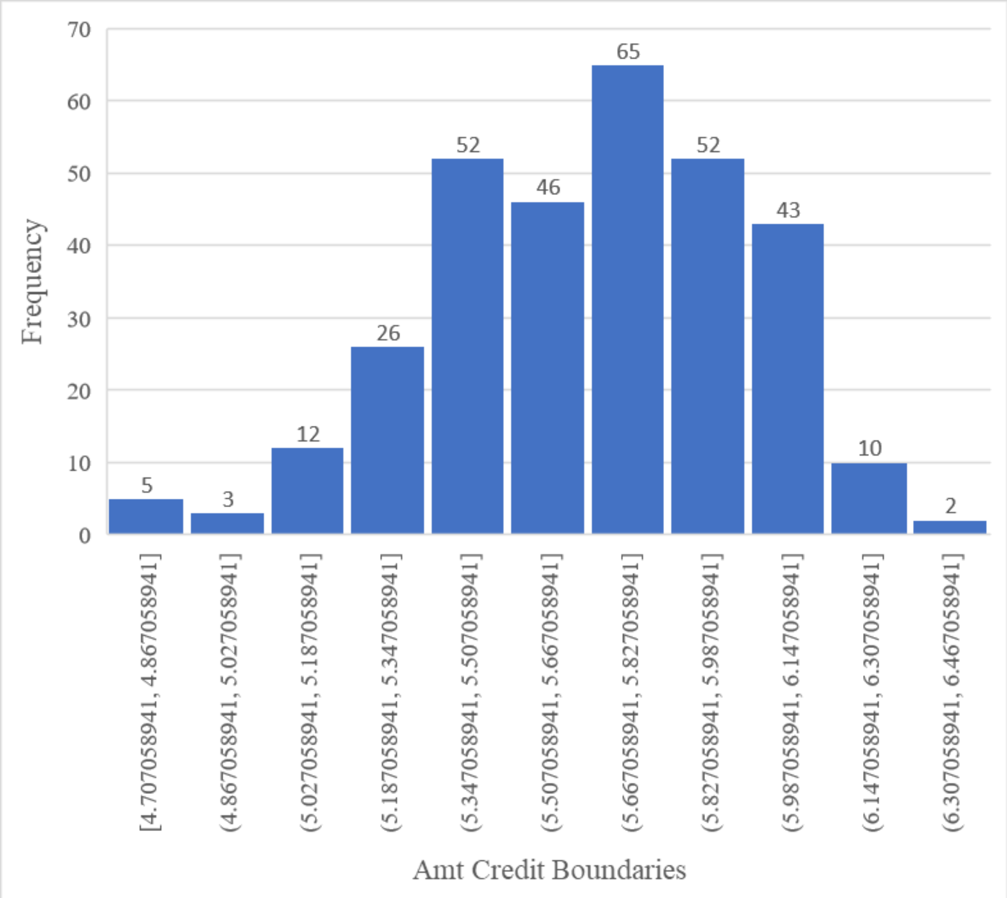
Figure 4.2 and Table 4.2 show the total annual income distribution of loan applicants. Among them, the income range with the highest proportion is (5.09, 5.20), accounting for 19.62% of the total sample. The amount in this range represents annual income INR 121,500 (MYR 6900) - INR 162,000 (MYR 9281). This means that most borrowers in this range have annual income between this amount.

On the contrary, the income range with the lowest proportion is the range with the highest total income (5.75, 5.86), > INR 693,000 (MYR 39,574), accounting for only 0.63%.

According to the report provided, the average monthly income in India ranges from INR 10,511 (MYR 602) to INR 15,000 (MYR 856) (Jain & Tambe, 2024). People with average income are the main loan customers of Indian banks.

4.3.3 Loan Profile (Amount Credit)

Figure 4.3 The Amt Credit



Source: Adopt from Secondary Data

Table 4.3 The Amt Credit

Amt Credit Boundaries	Frequency	Percentage
(4.71, 4.87)	5	1.58%
(4.87, 5.03)	3	0.95%
(5.03, 5.19)	12	3.80%
(5.19, 5.35)	26	8.23%
(5.35, 5.51)	52	16.46%
(5.51, 5.67)	46	14.56%
(5.67, 5.83)	65	20.57%
(5.83, 5.99)	52	16.46%

(5.99, 6.15)	43	13.61%
(6.15, 6.31)	10	3.16%
(6.31, 6.47)	2	0.63%
Total	316	100%

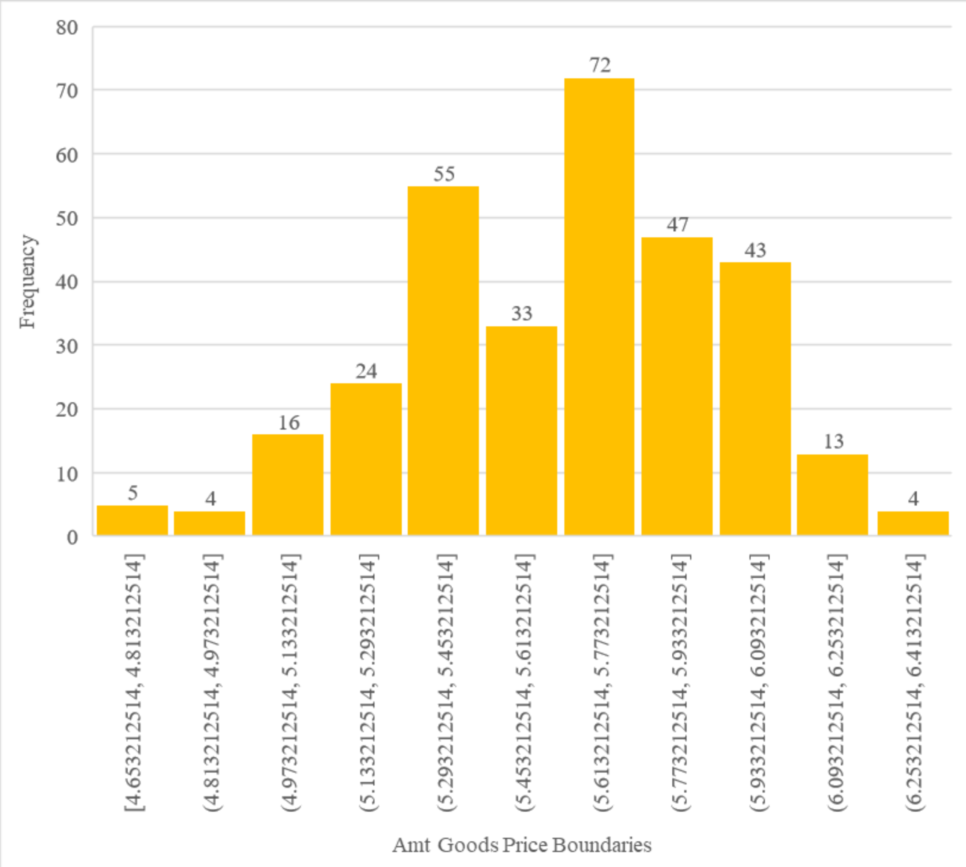
Source: Adopt from Secondary Data

Figure 4.3 and Table 4.3 show the borrower's credit limit (Amt Credit). Among them, the range with the highest proportion of credit limit (Annual) is (5.67, 5.83), INR 473,760 (MYR 27,053) - INR 679500 (MYR 38,802), accounting for approximately 20.57% of the total sample. The annual credit amount in this range is relatively large; at the same time, the original data shows that the annual income in this range is INR 47250 - 540,000. This shows that borrowers in this range can repay stably and do not borrow amounts beyond their financial capabilities. Secondly, the proportions of the (5.35, 5.51) and (5.83, 5.99) intervals are tied for second, with 53 people each, accounting for 16.61% of the total sample. The 2 intervals are before and after the highest proportion interval.

Finally, borrowers' credit limits are concentrated in the middle range. This suggests that this subset of borrowers in the sample have higher credit limits and may be more likely to obtain larger loans or lines of credit.

4.3.4 Financial Behaviour (Amount Goods Price)

Figure 4.4 The Amt Goods Price



Source: Adopt from Secondary Data

Table 4.4 The Goods Price

Amt Credit Boundaries	Frequency	Percentage
(4.65, 4.81)	5	1.58%
(4.81, 4.97)	4	1.27%
(4.97, 5.13)	16	5.06%
(5.13, 5.29)	24	7.59%
(5.29, 5.45)	55	17.41%
(5.45, 5.61)	33	10.44%
(5.61, 5.77)	72	22.78%
(5.77, 5.93)	47	14.87%
(5.93, 6.09)	43	13.61%
(6.09, 6.25)	13	4.11%

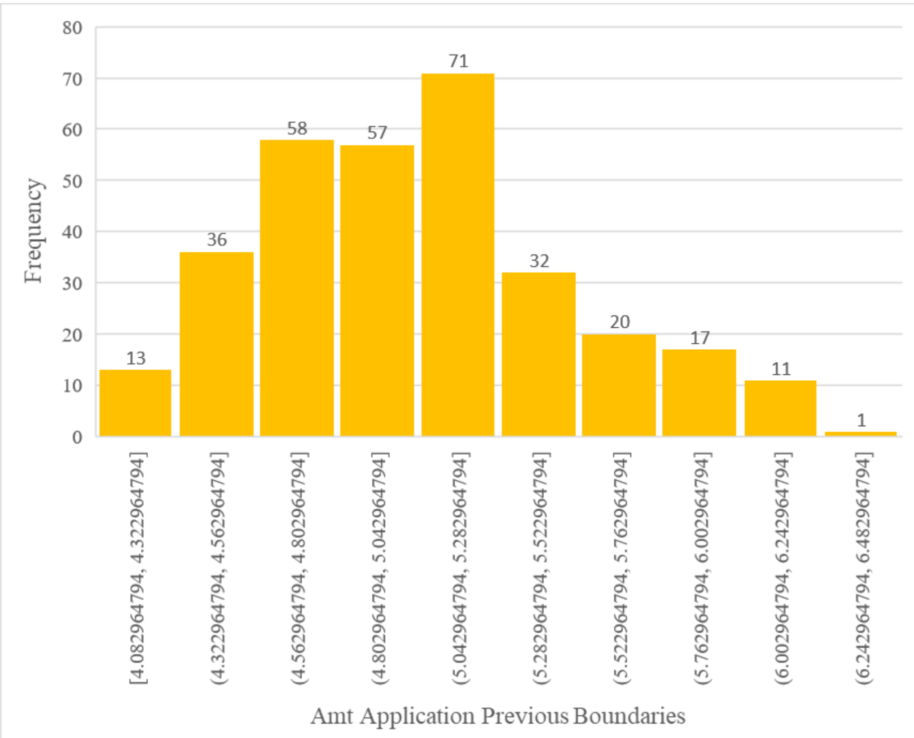
(6.25, 6.41)	4	1.27%
Total	316	100%

Source: Adopt from Secondary Data

According to the additional information provided by the original data, higher amounts are usually related to business development, house purchase, car purchase and other high-value assets; conversely, lower amounts are usually related to daily consumption. The distribution of Amount Goods Price boundaries is shown in Figure 4.4 and Table 4.4. The most common boundary range is (5.61, 5.77), with the highest ratio, INR 405,000 (MYR 23,135) - INR 585000 (MYR 33,418), which is 22.78%. Therefore, this range is an upper amount, indicating that these amounts are of use may be related to assets, business, repairs, etc.

4.3.5 Financial Needs (Amount Application Previous)

Figure 4.5 The Amt Application Previous



Source: Adopt from Secondary Data

Table 4.5 The Amt Application Previous

Amt Credit Boundaries	Frequency	Percentage
(4.08, 4.32)	13	4.11%
(4.32, 4.56)	36	11.39%
(4.56, 4.80)	58	18.35%
(4.80, 5.04)	57	18.04%
(5.04, 5.28)	71	22.47%
(5.28, 5.52)	32	10.13%
(5.52, 5.76)	20	6.33%
(5.76, 6.00)	17	5.38%
(6.00, 6.24)	11	3.48%
(6.24, 6.48)	1	0.32%
Total	316	100%

Source: Adopt from Secondary Data

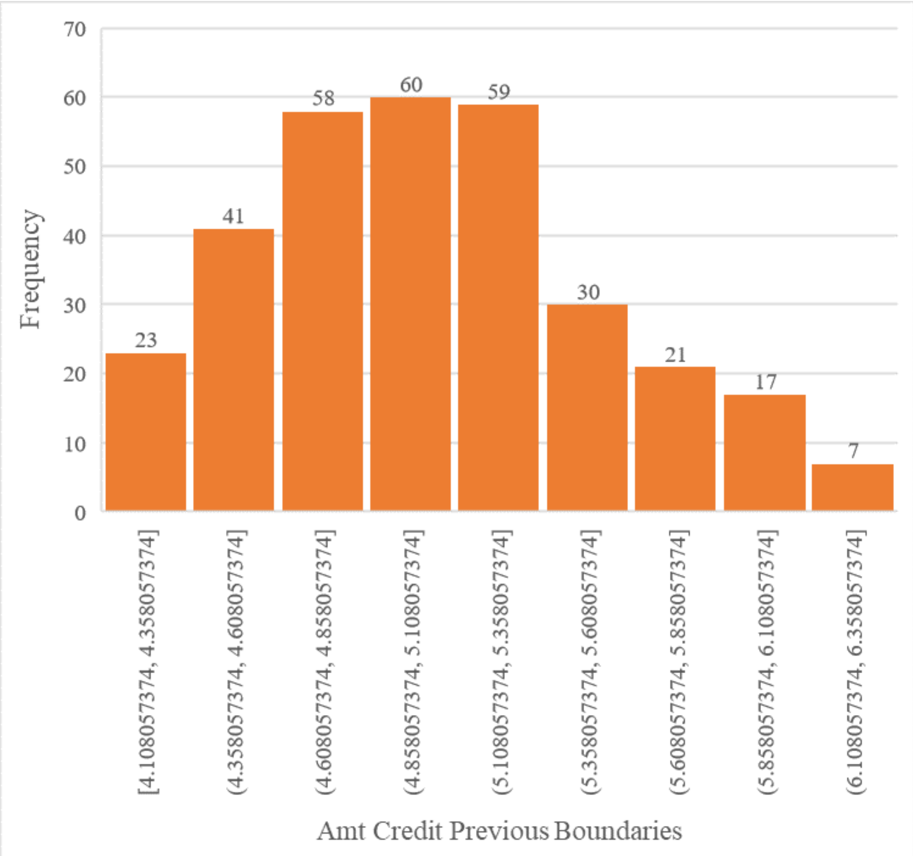
A borrower's previous application amounts can help understand their financial situation and credit history. Higher prior application amounts may indicate that the borrower has had greater financial need or borrowed amounts in the past and may mean that the borrower's financial situation is more complex.

Additionally, a higher priority application amount may indicate that the borrower may have a larger debt load or delinquencies on their credit history. For example, in the original data, we found that many borrowers have multiple borrowing histories; individual borrowers have huge historical borrowing amounts, and their backgrounds are mostly related to business development. For example, the SKID 102782 applicant used the money to purchase assets for business purposes. In the large sums he subsequently applied for again, it can also be found that he repurchased assets for business purposes. Therefore, the amount of past applications can also be used as one of the indicators to evaluate the borrower's credit record and repayment ability.

The distribution of Amt Application Previous Frontiers is shown in Figure 4.5 and Table 4.5. The most common boundary range is (5.04,5.28), INR 110,000 - INR 200,000, with a maximum ratio of 22.47%. The main population of this data is distributed between (4.56 - 5.28) INR 36,000 - INR 200,00, which is generally in the middle and lower range, which may reflect the demand and supply situation of people with middle and low incomes; therefore, the amount applied for is not large.

4.3.6 Payment History (Amount Credit Previous)

Figure 4.6 The Amt Credit Previous



Source: Adopt from Secondary Data

Table 4.6 The Amt Credit Previous

Amt Credit Boundaries	Frequency	Percentage
(4.11, 4.36)	23	7.28%
(4.36, 4.61)	41	12.97%

(4.61, 4.86)	58	18.35%
(4.86, 5.11)	60	18.99%
(5.11, 5.36)	59	18.67%
(5.36, 5.61)	30	9.49%
(5.61, 5.86)	21	6.65%
(5.86, 6.11)	17	5.38%
(6.11, 6.36)	7	2.22%
Total	316	100%

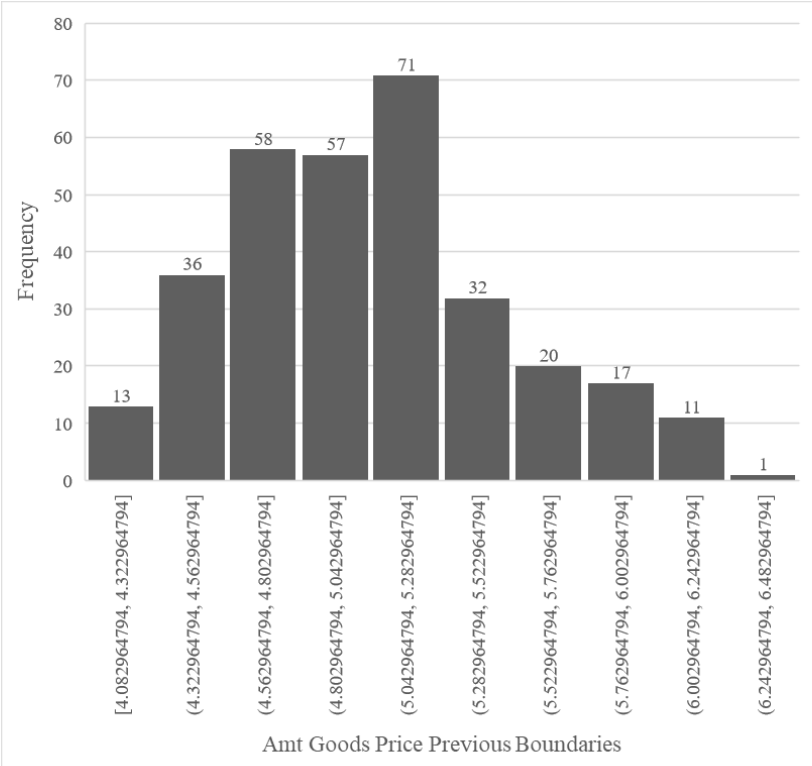
Source: Adopt from Secondary Data

A higher credit limit and a stable credit history usually mean that the borrower has a good credit history and credit ability. Changes in a borrower's previous credit limit may reflect changes in his or her financial situation, for example, an increase in the credit limit may indicate a credit rating improvement, while a reduction in credit lines may indicate a deterioration in financial conditions.

The distribution of Amount Credit Previous is shown in Figure 4.6 and Table 4.6. The most common boundary range is (4.86, 5.11), with the highest ratio of 18.99%; however, there are two ranges (4.61, 4.86) and (5.11, 5.36) that both have the closest ratio to (4.86, 5.11). As can be seen from Figure 4.6, the overall distribution of the three ranges is low and concentrated; this means that there may be the possibility of a credit rating reduction. This may be because they have a history of past dues, defaults, etc.

4.3.7 Purpose of Loan (Amt Goods Price Previous)

Figure 4.7 The Amt Goods Price Previous



Source: Adopt from Secondary Data

Table 4.7 The Amt Goods Price Previous

Amt Credit Boundaries	Frequency	Percentage
(4.08, 4.32)	13	4.11%
(4.32, 4.56)	36	11.39%
(4.56, 4.80)	58	18.35%
(4.80, 5.04)	57	18.04%
(5.04, 5.28)	71	22.47%
(5.28, 5.52)	32	10.13%
(5.52, 5.76)	20	6.33%
(5.76, 6.00)	17	5.38%
(6.00, 6.24)	11	3.48%
(6.24, 6.48)	1	0.32%

Total	316	100%

Source: Adopt from Secondary Data

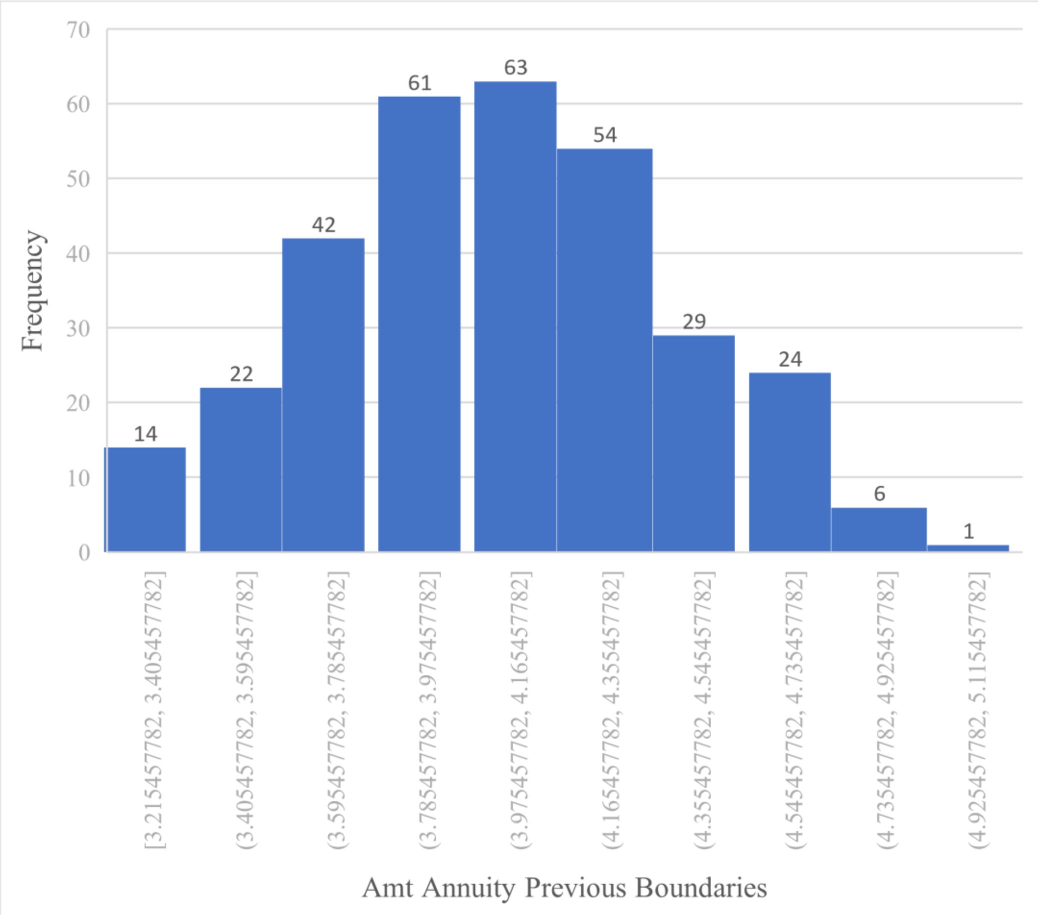
The amount of a borrower's previous commodity prices can provide important information about the borrower's behavior and financial condition. A higher commodity price amount may reflect a borrower's borrowing preferences and financial capabilities, while a lower commodity price amount may indicate credit risk or financial difficulties.

The distribution of Amt Goods Price Previous is shown in Figure 4.7 and Table 4.7. The most common boundary range is (5.04,5.28), INR109,660 - INR 191,000, which is 22.47%. This range is close to 5.0364 (mean) with a small gap, which means that borrowers in this range may use loan funds to meet different economic needs; at the same time, due to relatively stable economic conditions, there is no need to pursue high loan amounts.

Not only that, but the data also shows that the overall main population is obviously concentrated in the lower part, that is, (4.56 - 5.28). This may reflect the current lending trend in the market; due to the overall economic slowdown, people have greater demand for inferior goods, which has led to a surge in demand for low-cost purchases of inferior goods.

4.3.8 DV: Credit Score (Amount Annuity Previous)

Figure 4.8 The Amt Annuity Previous



Source: Adopt from Secondary Data

Table 4.8 The Annuity Previous

Amt Credit Boundaries	Frequency	Percentage
(3.22, 3.41)	14	4.43%
(3.41, 3.60)	22	6.96%
(3.60, 3.79)	42	13.29%
(3.79, 3.98)	61	19.30%
(3.98, 4.17)	63	19.94%
(4.17, 4.36)	54	17.09%
(4.36, 4.55)	29	9.18%
(4.55, 4.74)	24	7.59%

(4.74, 4.93)	6	1.90%
(4.93, 5.12)	1	0.32%
Total	316	100%

Source: Adopt from Secondary Data

Prior annuity amounts are the amounts the borrower has paid in the past. In this dependent variable, the borrower's past number of monthly payments provides some information. First, it reflects the borrower's ability to repay debt and its repayment summary.

The distribution of Amt Annuity Previous is shown in Figure 4.8 and Table

4.8. The overall boundary range does not exceed 5, compared with other IVs. The most common boundary ranges are (3.98, 4.17) and (3.79, 3.98), with the highest proportions being 19.94% and 19.30% respectively. This may indicate that the borrower's past monthly repayments have shown a lower average level, and there may be behavior such as late repayment.

4.4 Inferential Analysis

This research utilizes both Confirmatory Factor Analysis and Pearson correlation analysis to examine the connection between independent variables and dependent variables.

4.4.1 Confirmatory Factor Analysis

Table 4.9 Factor Analysis – Correlation Matrix

		FLAG OWN REALTY	AMT INCOME TOTAL	AMT CREDIT	AMT GOODS PRICE	AMT ANNUITY PREVIOUS	AMT APPLICATION PREVIOUS	AMT CREDIT PREVIOUS	AMT GOODS PRICE PREVIOUS
Correlation	FLAG OWN REALTY	1.000	0.125	-0.053	-0.046	0.068	0.094	0.091	0.094
	AMT INCOME TOTAL	0.125	1.000	0.404	0.422	0.281	0.271	0.251	0.271
	AMT CREDIT	-0.053	0.404	1.000	0.990	0.195	0.170	0.145	0.170
	AMT GOODS PRICE	-0.046	0.422	0.990	1.000	0.204	0.176	0.149	0.176
	AMT ANNUITY PREVIOUS	0.068	0.281	0.195	0.204	1.000	0.883	0.873	0.883
	AMT APPLICATION PREVIOUS	0.094	0.271	0.170	0.176	0.883	1.000	0.990	1.000
	AMT CREDIT PREVIOUS	0.091	0.251	0.145	0.149	0.873	0.990	1.000	0.990
	AMT GOODS PRICE PREVIOUS	0.094	0.271	0.170	0.176	0.883	1.000	0.990	1.000

Sources: Developed for Research (SPSS)

The correlation coefficient between Amt Income Total and Amt Annuity Previous is 0.281, indicating a positive relationship. This means that individuals with higher total income may receive higher annuity amounts from previous loans.

The correlation coefficient between Amt Credit and Amt Annuity Previous is 0.195, indicating that there is a certain positive relationship. This may mean a larger loan amount is required to cover the annuity payments on the previous loan. For example, an individual may need a larger loan to purchase a more expensive asset or make a larger investment.

The correlation coefficient between Amt Application Previous and Amt Annuity Previous is 0.883, indicating a strong positive correlation. This suggests that individuals or small businesses applying for larger loan amounts may face higher annuity payments.

Table 4.10 Factor Analysis - Communalities

Communalities		
	Initial	Extraction
FLAG OWN REALTY	1.000	0.920
AMT INCOME TOTAL	1.000	0.518
AMT CREDIT	1.000	0.947
AMT GOODS PRICE	1.000	0.954
AMT ANNUITY PREVIOUS	1.000	0.866
AMT APPLICATION PREVIOUS	**1.000**	**0.985**
AMT CREDIT PREVIOUS	1.000	0.976
AMT GOODS PRICE PREVIOUS	1.000	0.985

Sources: Developed for Research (SPSS)

According to the survey analysis of Shrestha (2021), the extraction value communalities must be least more than 0.5, where it should be suggesting the common variance in the data set. Therefore, the closer the value approaches 1, the stronger the correlation between the observed variable and the underlying factor.

a. *Flag Own Realty*

The results show that after extraction, the common factor variance is 0.920, indicating that approximately 92% of the variance can be explained by latent factors. This indicates a high correlation between Flag Own Realty and other variables.

b. *Amt Income Total*

The results show that the extracted common factor variance is only 0.518, indicating that only about 51.8% of the variance can be explained by the latent factors, but the correlation with other variables is relatively low.

c. *Amt Credit & Amt Goods Price*

These two IVs represent the loan amount and goods price respectively. The extracted common factor variances of these two variables are both high, 0.947 and 0.954 respectively, indicating that there is a high correlation between them and the latent factors, and about 95% of the variance can be explained by the latent factors.

d. *Amt Annuity Previous*

Amt Annuity Previous represents the amount of annuity that has been repaid previously. After extraction, its common factor variance is 0.866, indicating that approximately 86.6% of the variance can be explained by latent factors. This shows that there is also a certain correlation between this DV and other variables.

e. *Amt Application Previous, Amt Credit Previous & Amt Goods*

Price Previous Their extracted common factor variances are all high, 0.985, 0.976, and 0.985 respectively, indicating that there is a very high correlation between them and the latent factors, and about 98% of the variance can be explained by the latent factors.

Table 4.11 Component Matrix

	Component		
	1	2	3
FLAG OWN REALTY	0.111	-0.110	0.946
AMT INCOME TOTAL	0.438	0.457	0.342
AMT CREDIT	0.390	0.889	-0.064
AMT GOODS PRICE	0.399	0.890	-0.052
AMT ANNUITY PREVIOUS	0.910	-0.184	-0.063
AMT APPLICATION PREVIOUS	0.961	-0.243	-0.051
AMT CREDIT PREVIOUS	0.949	-0.268	-0.056
AMT GOODS PRICE PREVIOUS	0.961	-0.243	-0.051

Sources: Developed for Research (SPSS)

Table 4.12 Pattern Matrix

	Component 1	Component 2	Component 3
FLAG OWN REALTY	-0.042	-0.066	0.967
AMT INCOME TOTAL	0.121	0.569	0.328
AMT CREDIT	-0.036	0.982	-0.111
AMT GOODS PRICE	-0.031	0.985	-0.099
AMT ANNUITY PREVIOUS	0.925	0.036	-0.025
AMT APPLICATION PREVIOUS	0.996	-0.011	-0.007
AMT CREDIT PREVIOUS	0.998	-0.039	-0.011
AMT GOODS PRICE PREVIOUS	0.996	-0.011	-0.007

Sources: Developed for Research (SPSS)

First Component

Indicators such as Property Ownership Flag, Total Income Amount, Credit Amount, Goods Price Amount, Previous Annuity Amount, Previous Application Amount, Previous Credit Amount, and Previous Goods Price Amount exhibit significant weights on the primary component.

Second Component

Amt Income Total, Amt Credit, and Amt Goods Price have relatively high loadings on the second component, with loading values close to 1 reflecting underlying factors of individual loan size and merchandise purchase behavior.

Third Component

Flag Own Realty has the highest loading value on the third component, where may be related to another independent underlying factor, namely asset condition or related factors such as financial stability.

Table 4.13 Total Variance Explained

Total Variance Explained							
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings[a]
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	4.091	51.140	51.140	4.091	51.140	51.140	3.972
2	2.028	25.346	76.486	2.028	25.346	76.486	2.452
3	1.031	12.890	89.376	1.031	12.890	89.376	1.144
4	0.655	8.190	97.566				
5	0.172	2.151	99.717				
6	0.013	0.162	99.878				
7	0.010	0.122	100.000				
8	8.693E-18	1.087E-16	100.000				

Sources: Developed for Research (SPSS)

The total variance explained is a key indicator in the factor analysis results, which indicates the percentage of the total variance of the original variables that can be explained by the number of selected factors (Kline, 2014).

For the first factor, the initial eigenvalue was 4.091, which explained 51.140% of the total variance and accounted for 51.140% of the cumulative percentage, indicating that the first factor explained a large portion of the variability in the data well. The second factor (2.028) explains 25.346% of the total variance and accounts for 76.486% of the cumulative percentage. The third factor (1.031) explains 12.890% of the total variance and accounts for 89.376% of the cumulative percentage. Although the second and third factors explain less variance than the first factor, it still adds a certain degree of ability to explain the data. Hatcher and O'Rourke (2013) observed that researchers need to ensure that the cumulative percentage of variance reaches a minimum of 70% when they employ it as a criterion for components. Hence, the cumulative percent of variance for the three factors are above acceptable range.

4.4.2 Pearson Correlation Analysis

Table 4.14: Pearson Correlation Matrix

Correlations									
		FLAG OWN REALTY	AMT INCOME TOTAL	AMT CREDIT	AMT GOODS PRICE	**AMT ANNUITY PREVIOUS**	AMT APPLICATION PREVIOUS	AMT CREDIT PREVIOUS	AMT GOODS PRICE PREVIOUS
FLAG OWN REALTY	Pearson Correlation	1	.122*	-0.051	-0.043	**0.060**	0.094	0.080	0.094
	Sig. (2-tailed)		0.030	0.363	0.444	**0.281**	0.095	0.155	0.095
	N	319	319	319	319	**319**	316	319	316
AMT INCOME TOTAL	Pearson Correlation	.122*	1	.406**	.424**	**.285****	.271**	.256**	.271**
	Sig. (2-tailed)	0.030		0.000	0.000	**0.000**	0.000	0.000	0.000
	N	319	319	319	319	**319**	316	319	316
AMT CREDIT	Pearson Correlation	-0.051	.406**	1	.990**	**.199****	.170**	.149**	.170**
	Sig. (2-tailed)	0.363	0.000		0.000	**0.000**	0.002	0.008	0.002
	N	319	319	319	319	**319**	316	319	316
AMT GOODS PRICE	Pearson Correlation	-0.043	.424**	.990**	1	**.206****	.176**	.152**	.176**
	Sig. (2-tailed)	0.444	0.000	0.000		**0.000**	0.002	0.007	0.002

	N	319	319	319	319	**319**	316	319	316
AMT ANNUITY PREVIOUS	**Pearson Correlation**	**0.060**	**.285****	**.199****	**.206****	**1**	**.883****	**.873****	**.883****
	Sig. (2-tailed)	**0.281**	**0.000**	**0.000**	**0.000**		**0.000**	**0.000**	**0.000**
	N	**319**	**319**	**319**	**319**	**319**	**316**	**319**	**316**
AMT APPLICATION PREVIOUS	Pearson Correlation	0.094	.271**	.170**	.176**	**.883****	1	.990**	1.000**
	Sig. (2-tailed)	0.095	0.000	0.002	0.002	**0.000**		0.000	0.000
	N	316	316	316	316	**316**	316	316	316
AMT CREDIT PREVIOUS	Pearson Correlation	0.080	.256**	.149**	.152**	**.873****	.990**	1	.990**
	Sig. (2-tailed)	0.155	0.000	0.008	0.007	**0.000**	0.000		0.000
	N	319	319	319	319	**319**	316	319	316
AMT GOODS PRICE PREVIOUS	Pearson Correlation	0.094	.271**	.170**	.176**	**.883****	1.000**	.990**	1
	Sig. (2-tailed)	0.095	0.000	0.002	0.002	**0.000**	0.000	0.000	
	N	316	316	316	316	**316**	316	316	316
*. Correlation is significant at the 0.05 level (2-tailed).									
**. Correlation is significant at the 0.01 level (2-tailed).									

Sources: Developed for Research (SPSS)

By having P value below 0.05, whole independent variables (except for Flag Own Realty) for this research have a solid relationship with the credit score. Based on the result, Amount Application Previous, Amount Credit, and Amount of Goods Price Previous are positively associated; meanwhile, Flag Own Realty is negatively associated.

4.5 Hypothesis Conclusion

Based on the provided Pearson correlation coefficient matrix, we can draw the following findings.

Table 4.15 Hypothesis Conclusion

Independent Variables	Hypothesis Testing	Result	Significance	Pearson Correlation
AMT APPLICATION PREVIOUS (Financial Needs)	H5: The Relationship between Financial Needs and Credit Score	Accept	Significant	0.883**
AMT GOODS PRICE PREVIOUS (Purpose of Loan)	H6: The Relationship between Purpose of Loan and Credit Score	Accept	Significant	0.883**
AMT CREDIT PREVIOUS (Payment History)	H7: The Relationship between Payment History and Credit Score	Accept	Significant	0.873**
AMT INCOME TOTAL (Income Level)	H2: The Relationship between Income Level and Credit Score	Accept	Significant	0.285**
AMT GOODS PRICE (Financial Behavior)	H4: The Relationship between Financial Behavior and Credit Score	Accept	Significant	0.206**
AMT CREDIT (Loan Profile)	H3: The Relationship between Loan Profile and Credit Score	Accept	Significant	0.199**

Sources: Developed for Research (SPSS)

Chapter 5: Discussion, Conclusion, and Implications

5.1 Introduction

This chapter summarized the results of the investigation conducted in chapter 4, aiming to address the research questions and objectives, analyze the study's implications, recognize its constraints, propose avenues for future research, and draw conclusions.

5.2 Discussion on Major Findings

5.2.1 Discussion on 1st Research Objective – To identify the factors influencing the credit score improvement for individuals and small businesses.

According to the result in Chapter 4, 6 variables in this study are significant and remaining 1 is not supported.

Overall, Financial Needs and Purpose of Loan show a high positive correlation with credit scores, but the loan amount of the main user is lower. This may be due to the low overall income level in India, which leads to an increase in demand for inferior goods and services. And as this type of demand increases, borrowers may also pursue inferior types of assets for self-use or commercial use. Asquith, Mast, and Reed (2020) concluded that new construction in low-income areas absorbs households from low- to high-income households, driven by huge supply effects due to lower rents and property prices.

In addition, payment history shows a high positive correlation with credit scores. Through the previous credit amount that has been repaid, it is found that the loan amount of the main user is medium to low. Through the entire loan that has been repaid, it can be found that these records have established the basis for a good credit score; not only that, but the main user may also be more inclined to choose short-term or small loans instead of larger loans. Although the loan amounts are lower, these loans may help build a good credit history.

Income level has a positive correlation with credit score, but the correlation is low. The possible reason is that income level cannot directly prove the borrower's willingness to repay and financial behavior; but it can still be used as one of the borrowing indicators.

In addition, asset and liability status did not show a positive or negative correlation with the credit score and were rejected. The reason is that most borrowers have low overall income and also own properties. These properties may be located in low-price areas or belong to sub-class HDB housing (refer to Singapore HDB), and the future development trend of these areas is unclear. Therefore, it cannot be used as the primary review criterion.

5.2.2 Discussion on 2nd Research Objectives – To provide a guideline of Digital Bank Credit Scoring for Small Businesses and Individuals in Malaysia.

First, by highlighting key influencing factors, the findings point to factors such as loan purpose and payment history as having a significant impact on credit scores. It is recommended that digital banks should prioritize these factors when developing credit scoring models to assess borrowers' credit risks more accurately.

In addition, although income level has a low correlation with credit scores, it is still an important factor. When digital banks evaluate borrowers' credit risks, they should comprehensively consider income levels and loan needs, and make reasonable trade-offs based on actual circumstances.

Third, emphasize the critical role of loan history in establishing a good credit score. Borrowers are advised to pay attention to maintaining a good payment history when applying for a loan, as this can help improve their credit score and increase their chances of getting a loan.

5.3 Implications

This section will cover several implications, with theoretical and practical implications which both are mainly focused on.

5.3.1 Practical Implications

Prioritize the adaptability of Indian data to the current situation in Malaysia. The research data may reflect some global trends, such as the popularity of digital financial services, borrowers' credit behavior patterns, etc., especially compared with the global (67%), up to 87% (Lin, 2023). Not only that, but digital banks can also learn from the success or failure cases shown in the Indian data and apply them to the Malaysian context.

The purpose of the guideline is to establish the user's credit score; therefore, the focus of the guideline will focus on important variables as the main considerations.

Firstly, from the perspective of digital banks, by analysing the financial needs of individuals and small businesses and their relationship with credit scores, digital banks can design personalized loan products based on the characteristics of different customer groups. For example, for customers with lower credit scores, flexible repayment plans and more relaxed loan terms can be designed to improve their chances of obtaining loans and help them improve their credit scores. Through guidelines, important customer specifications related to guidelines can be directly extracted from the bank database and directly reviewed through a multi-objective model (Firouzabadi, Taghavifard, Sajjadi, & Soufi, 2018).

Secondly, from the perspective of customers, You can establish and maintain a good credit record through several methods, such as using a

digital bank's savings account and demonstrating financial behavior and financial needs through consumption records; second, demonstrating stable repayment through the accumulation of multiple small loans. Records and financial behavior, for example, vendors can take loans to purchase different types of low-cost machines to demonstrate the usefulness of loans. Third, use digital banking services such as credit cards or debit cards for tax repayment, including personal income tax, commercial tax, etc.; the amount of tax and related information can demonstrate the financial and market capabilities of individuals or small businesses, and financial behavior. Of course, repaying your loan on time and avoiding overdue payments can improve your chances of getting a loan next time and get more favourable loan terms and interest rates.

5.3.2 Theoretical Implications

This research can provide an important reference for relevant financial regulatory agencies in Malaysia to formulate financial technology policies. Due to the popularization of new business models (Digital Bank) in Malaysia, most financial regulations may still apply to physical banks or financial institutions; therefore, the current regulations may not fully cover all needs. The importance of these regulations will change the landscape of payment systems, affecting issues such as monetary policy (Marques, et al., 2021).

In addition, this research may provide new perspectives and understandings for the development of credit score modelling theory, thereby enriching and improving the existing theoretical framework. For example, based on the research results, recommendations may be made to improve and optimize existing credit scoring models to make the models more accurate and effective. This research may provide new insights into model variable selection, weight adjustment, model structure, etc., thereby improving the predictive ability and robustness of credit scoring models. For example, most financial institutions weight repayment history and income to measure the market performance of individuals or small businesses.

5.4 Limitations and Recommendations for Future Research

This section will be discussed further in limitations discovered and recommendations for future research development.

5.4.1 Limitation – Regional limitation

The study data come primarily from India, so generalizability to other countries or regions may be limited. The economic, financial, and cultural environments may differ between regions, so the applicability of the findings to other countries or regions may be affected. The first reason is that there are differences in the concept of consumer culture between India and Malaysia, and there are also differences in the average income levels of the overall people. Additionally, there are differences in the overall economic structure between the two countries. Due to India's long-term industrialization dominated by manufacturing, compared with Malaysia's structure dominated by agriculture, construction, and service industries, there are certain differences between the two sides (Brownlow, 2023; Farouq, 2023).

5.4.2 Limitation - Causality

Causality refers to a change in one variable (independent variable) causing a change in another variable (dependent variable). Determining cause and effect is crucial in research because it helps us understand the true impact of events, not just correlations. However, in many cases, an observed correlation does not imply causation because there may be other unaccounted variables or reverse causation. In this study, although we may observe correlations between some variables, such as the relationship between financial needs and credit scores, we cannot directly conclude that this relationship is causal. To establish a causal relationship, an experimental research design is needed to determine the real cause of the impact on the dependent variable by controlling the independent variables and randomly assigning treatments.

5.4.3 Recommendations - Regional Limitation

First, in order to improve the applicability and reliability of the research results, it is recommended that future research can conduct comparative analysis by using data from multiple countries or regions. This allows for a more comprehensive understanding of differences and similarities between regions and improves the generalizability of the findings. In addition, conduct cross-national research and fully consider the cultural differences between different countries or regions, such as the consumer culture, values, lifestyles, etc. of the target country or region to gain an in-depth understanding, and adjust the research design and analysis methods to ensure the validity of the research results. Accuracy and reliability. The most similar example to Malaysia is Singapore. Singapore's economic structure, humanities, consumption concepts, laws and regulations are all very similar to Malaysia.

5.4.4 Recommendations – Causality

First, conduct long-term tracking studies that track changes in financial behavior and credit scores of individuals or groups over an extended period of time. Secondly, analyze the long-term dynamic relationship between variables and explore the long-term impact of financial needs, payment history and other factors on credit scores. Finally, through long-term follow-up research, the causal relationship between variables can be better understood and long-term guidance and suggestions can be provided for digital banks.

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